Check for updates

Assessing Vegetation Function with Imaging Spectroscopy

J. A. Gamon[1,2] · **B. Somers[3]** · **Z. Malenovský[4,5,6]** · **E. M. Middleton[6]** · **U. Rascher[7]** ·
M. E. Schaepman[8,9]

Abstract

Healthy vegetation function supports diverse biological communities and ecosystem processes, and provides crops, forest products, forage, and countless other benefits. Vegetation function can be assessed by examining dynamic processes and by evaluating plant traits, which themselves are dynamic. Using both trait-based and process-based approaches, spectroscopy can assess vegetation function at multiple scales using a variety of sensors and platforms ranging from proximal to airborne and satellite measurements. Since spectroscopic data are defined by the instruments and platforms available, along with their corresponding spatial, temporal and spectral scales, and since these scales may not always match those of the function of interest, consideration of scale is a necessary focus. For a full understanding of vegetation processes, combined (multi-scale) sampling methods using empirical and theoretical approaches are required, along with improved informatics.

REVISED PROOF

✉ J. A. Gamon
  jgamon@gmail.com

1 Departments of Earth and Atmospheric Sciences & Biological Sciences, University of Alberta, Edmonton, Alberta T6G 2E1, Canada

2 School of Natural Resources, University of Nebraska, Lincoln, NE 68583, USA

3 Department of Earth and Environmental Sciences, Katholieke Universiteit Leuven (KU Leuven), 3001 Leuven, Belgium

4 Surveying and Spatial Sciences Group, School of Technology Environments and Design, University of Tasmania, Private Bag 76, Hobart, TAS 7001, Australia

5 Remote Sensing Department, Global Change Research Institute CAS, Bělidla 986/4a, 60300 Brno, Czech Republic

6 Biospheric Sciences Laboratory, NASA Goddard Space Flight Center, 8800 Greenbelt Rd, Greenbelt, MD 20771, USA

7 Institute of Bio- and Geosciences, IBG-2: Plant Sciences, Forschungszentrum Jülich, Wilhelm-Johnen-Straße, 52425 Jülich, Germany

8 Remote Sensing Laboratories, Department of Geography, University of Zurich, Winterthurerstrasse 190, 8057 Zurich, Switzerland

9 University Research Priority Program on Global Change and Biodiversity, University of Zurich, Winterthurerstrasse 190, 8057 Zurich, Switzerland

1 Introduction

Vegetation plays a crucial role in many Earth system processes, including carbon and water cycling, biogeochemistry, and climate regulation. Additionally, plants provide humans with a wide range of important goods and services, ranging from forest products and fodder to food production. Our society and economy depend upon the healthy function of plants as well as the resilience of ecosystems of which they are a part. Remote sensing is playing an increasingly important role in monitoring, understanding, and maintaining these critical functions.

From a remote sensing perspective, vegetation *function* can have several meanings. One definition refers to the detection or quantification of plant *traits*, structural, physiological, biochemical, or phenological attributes that represent plant functional adaptations or reveal underlying plant ecophysiological processes (Kattge et al. 2011). A complementary definition of vegetation function addresses the *dynamics* of essential physiological, or ecological processes themselves. This definition emphasizes *variation* in key processes over time and space and implies that traits themselves can be dynamic.

In this review, we consider both trait- and process-based approaches used to assess plant function, and explore the history, promise and challenge of integrating these approaches in the context of optical remote sensing. The primary focus is on optical measurements, including spectral reflectance and fluorescence sampled with spectrometers, realizing that other types of remote sensing are also useful. Since our ability to detect plant function is scale-dependent, we start with a brief discussion of scale. Next, we review plant functional traits detectable with remote sensing, followed by a consideration of proximal and airborne remote sensing. We then discuss how global satellite remote sensing has been applied to vegetation assessment along with a presentation of new directions in satellite applications. We conclude with current challenges and opportunities, and provide suggestions and directions that are likely to further advance the study of vegetation function.

2 The Concept of Scale

Several aspects of scale, including spatial, temporal, spectral, and biological dimensions, are relevant to any discussion of detecting vegetation function with remote sensing. The dimensions of scale are often intertwined. At finer temporal and spatial scales, underlying mechanisms or traits are best revealed, often requiring fine spectral scales. At progressively larger scales, vegetation function represents the operation of many fine-scale properties and processes that may combine in complex ways due to nonlinear responses and intricate feedbacks. Thus, to a large extent, sampling scale determines which processes are detectable and how. Consequently, any remote sensing observation of vegetation function should include a consideration of scale, with attention to underlying mechanisms at finer scales and resulting emergent properties at larger scales.

Using the example of photosynthesis, a wide range of sampling approaches can be applied according to the particular process of interest and observational scale required (Fig. 1). At the leaf level, ontogenetic and regulatory processes, and corresponding traits, are detectable using proximal spectroscopy and chamber gas exchange measurements (Gamon et al. 1997; Gamon and Surfus 1999). At the canopy level, ranging from individual crowns to more complex plant stands, airborne spectroscopy can be applied to monitor
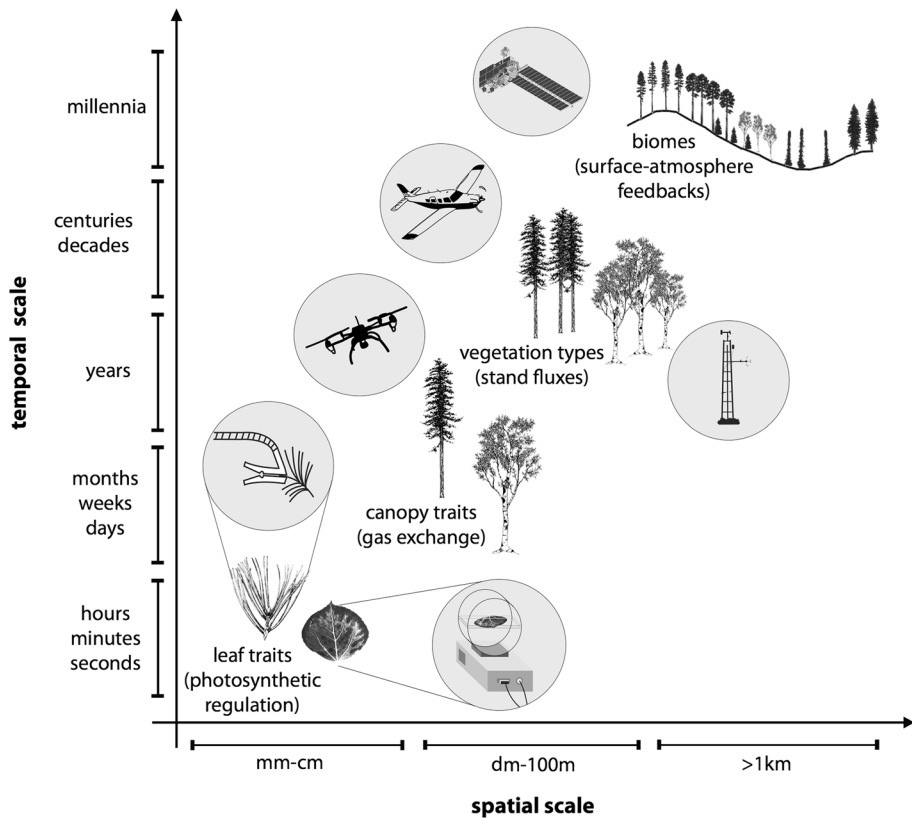
Fig. 1 Depiction of plant traits (and function) at different spatial and temporal scales. In this example of photosynthetic carbon uptake for evergreen and deciduous trees, relevant traits, corresponding functional processes, and measurement methods and terminology vary with scale (as described in the text) as well as with vegetation type (e.g., evergreen or deciduous) (Table 1). Several measurement approaches are indicated, showing spectroscopic methods in the upper left circles, and corresponding gas exchange methods in the lower right circles. Spatial and temporal scales indicated on the axes are approximate, depicting *relative* rather than absolute values, and refer to the processes and traits, not the measurements, which often do not match the spatial or temporal scales of the relevant processes and traits depicted, leading to scale mismatches

64 ecosystem photosynthesis and evapotranspiration (Fuentes et al. 2006), often measured
65 independently using eddy covariance. At stand to biome scales, airborne or satellite remote
66 sensing methods can detect changing vegetation productivity using optical or thermal prop-
67 erties, informing us of larger implications, such as altered vegetation productivity result-
68 ing from disease (Zarco-Tejada et al. 2018), plant invasion (Asner and Vitousek 2005),
69 or widespread disturbance and climate change (Goetz et al. 2005). At stand to global
70 scales, remote sensing can inform us of vegetation biophysical properties needed to under-
71 stand emergent processes, such as the influence of surface–atmosphere mass and energy
72 exchange on our atmosphere and climate (Bonan et al. 2002, 2003).

73 The topic of *how to scale*, or how we understand complex processes across scales,
74 has been well discussed from a variety of perspectives (Levin 1992; Ehleringer and Field
75 1993; Quattrochi and Goodchild 1997; Enquist et al. 2015), providing useful insights into
76 vegetation functional assessment. A proper study of function should consider processes

| Journal : **SmallCondensed 10712** | Article No : **9511** | Pages : **25** | MS Code : **GEOP-D-18-00002** | Dispatch : **11-2-2019** |

Surveys in Geophysics

at multiple scales, typically one level below to one level above the key process being observed (de Wit 1970, as discussed in Jarvis 1993), illustrating the importance of multi-scale sampling strategies (Fig. 1). A sampling strategy should first consider the patch size or length scale (Levin 1992) of the particular process in question. Ideally, remote sensing of vegetation function involves detecting traits (functional attributes) or processes defined at a particular length scale (or patch size) and temporal scale, and matching these scales with the instrument's spatial and temporal resolution and extent. In practice, this is often difficult due to the many sensors, traits, and scales involved and due to the scale mismatch between sensors' technical capabilities and the questions of interest (Fig. 1; Table 1). Due to these technical limitations, the fundamental sampling rules acknowledging effects of scale are often violated in remote sensing. This challenge of scale, often represented as the mismatch between field sampling and remote sensing, has sometimes limited the engagement of terrestrial ecologists or biologists with remote sensing, but is being rectified as the remote sensing capabilities and scaling methodologies evolve.

An important point emerging from this discussion is that there is no single, universally applicable scale for functional studies using remote sensing. Because each remote sensing instrument and platform has a defined sampling scale, often constrained by engineering requirements and physical laws, and because the spatial and temporal resolutions of different remote sensing methods do not always match the operational scale of the vegetation process of interest, multiple platforms and sampling scales should be considered, and additional methods are often needed. These methods may involve "upscaling," the extrapolation from small to large scales through biophysical models or statistical methods (Jung et al. 2011), or "downscaling," the inversion of models or interpretation of large-scale patterns in terms of underlying fine-scale processes (Jacquemoud et al. 2009). Additionally, a nested sampling protocol (Fig. 1), rather than a single remote sensing platform or approach, can improve our understanding of function, as is often used in remote sensing field campaigns (e.g., Sellers et al. 1997). With the proper attention to scale a remote sensing campaign can reveal information regarding underlying mechanisms and emergent properties associated with a particular vegetation function. How and what we detect with remote sensing, including the "best" sampling strategy, can depend on the specific question or hypothesis to be tested, the observer's disciplinary background, the technology at hand, and the realism of the scaling model with respect to the relevant physiological and biophysical processes. Challenges in scaling imaging spectroscopy observations from leaves to vegetation canopies, including topics of natural variability and measurement uncertainty, are further described by Malenovský et al. (2019) (this issue).

3 Vegetation Functional Traits

Spectral reflectance offers a powerful alternative to traditional methods of understanding vegetation function because it provides a rapid, consistent, repeatable, nondestructive, and objective sampling method to assess plant traits (functional attributes) from optical properties (Gamon and Surfus 1999). These traits provide information on plant structure, water, and biochemical content (Fig. 2). Consequently, one way to assess vegetation function with remote sensing relies on the concept of plant traits, which can be described at a range of scales (Table 1). Most leaf and plant traits influence vegetation optical properties either directly or indirectly, allowing functional assessment from spectral reflectance and transmittance (Cavender-Bares et al. 2017).

Surveys in Geophysics

Table 1 Examples of plant functional attributes and their relevant scales (leaf to landscape) that can be addressed using spectroscopy along with relevant references

Functional role (scales)	Traits	References
Gross primary production and energy balance (Canopy—Landscape)	Leaf area index (LAI)	Street et al. (2007)
	Leaf angle distribution (LAD)	Wang et al. (2007)
	Fraction of PAR absorbed (fPAR)	Myneni et al. (2002)
	Albedo	Ollinger et al. (2008), Williamson et al. (2016)
	Surface temperature	Schull et al. (2015)
	Canopy structure and greenness (NDVI, EVI, NIRv)	Huete et al. (2002), Badgley et al. (2017)
Photosynthetic rate, light-use efficiency (Leaf—Stand)	Nitrogen content	Reich et al. (1998)
	Specific leaf area (SLA)	Reich et al. (1998), Wright et al. (2004)
	Xanthophyll cycle activity (PRI)	Gamon et al. (2001), Gamon et al. (1997)
	Chlorophyll and carotenoid pigment levels (CCI)	Gamon et al. (2016)
	Solar-induced chlorophyll fluorescence (SIF)	Porcar-Castell et al. (2014), Drusch et al. (2017)
	Maximum carboxylation rate (Vcmax)	Serbin et al. (2012), Serbin et al. (2015)
Biogeochemical cycling (Leaf)	Nitrogen content	Singh et al. (2015)
	Lignin and cellulose content	Singh et al. (2015)
	Leaf water content	Serrano et al. (2000), Sims and Gamon (2003)
	Specific leaf area (SLA)	Reich et al. (1998), Wright et al. (2004)
Stress indication (Leaf—Stand)	Pigment levels (PRI, CCI)	Gamon et al. (2016)
	Leaf area index (LAI)	Battaglia et al. (1998)
	Leaf angle distribution (LAD)	Ehleringer and Comstock (1987)
	Foliar water content	Serrano et al. (2000), Sims and Gamon (2003)
	Maximum carboxylation rate (Vcmax)	Serbin et al. (2012), Serbin et al. (2015)
	Albedo	Teuling and Seneviratne (2008)
	Surface temperature	Schull et al. (2015)
	Solar-induced chlorophyll fluorescence (SIF)	Porcar-Castell et al. (2014)

At the coarser scales (top of table), these attributes are often termed "vegetation biophysical parameters," whereas at the finer scales (moving down the table), many of these attributes are often considered "leaf traits." In reality, there is some overlap across scales, with these attributes providing a continuum of approaches to assessing function. Examples of several vegetation indices useful for functional assessment are also listed, including *NDVI* normalized difference vegetation index, *EVI* enhanced vegetation index, *NIRv* near-infrared reflectance of terrestrial vegetation, *PRI* photochemical reflectance index, *CCI* chlorophyll/carotenoid index, *SIF* solar-induced fluorescence
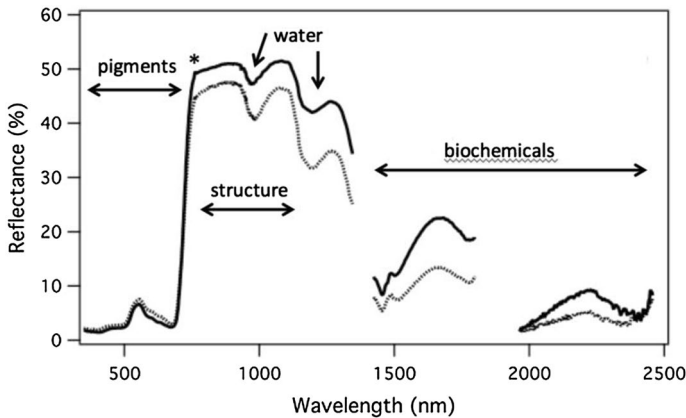
Fig. 2 Canopy reflectance spectra for deciduous poplar (*Populus balsamifera,* solid line) and evergreen spruce (*Picea glauca, dotted line*) canopies, showing spectral regions with information on pigment content, water content, biochemical content, and leaf or canopy structure. Alternatively, full-spectral information can be used to derive these and other leaf traits, as discussed in the text. Asterisk (*) indicates the location of the O_2-A band (fluorescence signal). Data gaps occur in wavelengths of strong atmospheric water absorption. Tree seedlings, sampled June 22, 2016, with a field spectrometer (PSR-3500, Spectral Evolution, Lawrence, MA, USA), in Edmonton, Alberta, Canada

There is a rich literature on plant traits at the leaf scale, much of which is now being related to leaf optical properties via reflectance spectra (e.g., Serbin et al. 2014). Leaf traits are often defined in terms of foliar constituents (e.g., biochemical or water content), or in terms of leaf structure (e.g., surface area, thickness, specific leaf area, or mass per area) (Cornelissen et al. 2003; Kattge et al. 2011; Homolová et al. 2013). Alternatively, leaf traits can be described in more direct functional and dynamic terms, including carboxylation potential, Vcmax (Serbin et al. 2012), photosynthetic rates, or radiation-use efficiency (Gamon et al. 1997). Remotely sensed data do not always map directly onto plant functional traits. Instead, leaf and plant traits can be considered latent variables best represented by transformations or linear combinations of multiple spectral features (Feilhauer et al. 2017). While not all traits are equally retrievable by remote sensing, many hidden traits can be correlated with more accessible traits, facilitating their characterization even when they cannot be directly detected with spectroscopic methods. In these cases, the functional connections between reflectance spectra and functional properties may not yet be entirely clear. Part of the power of spectra for assessing traits is that they provide information from many wavelengths, sometimes into a single metric as represented by a spectral index, or using many wavelengths simultaneously as depicted in a coefficient spectrum (Serbin et al. 2014).

In addition to leaf traits, functionally important vegetation properties can also be defined at larger scales (e.g., canopy traits, vegetation types, and biomes), and these categories can often be viewed as aggregations of underlying leaf or plant traits (van Bodegom et al. 2014). For example, deciduous and evergreen vegetation types tend to have distinct associations of leaf traits that are spectrally discernable (Gamon et al. 1997) (Figs. 1, 2). A clear understanding of canopy and stand structure is needed to understand the "scaleability" of leaf traits, which may depend on the particular trait and context, and can vary with vegetation type. For example, under the right conditions of uniform, closed vegetation stands, xanthophyll cycle pigment activity (an indicator

of photosynthetic light-use efficiency) can be directly detected at larger scales (Gamon and Qiu 1999; Stylinski et al. 2002), offering the possibility of stand-scale assessment of photosynthesis using aircraft or satellite remote sensing. However, complex and dynamic canopy structure can readily confound detection of this leaf photoprotective signal (Barton and North 2001; Gitelson et al. 2017). Consequently, accounting for changing Sun angle, view angle, and canopy structure can often improve the interpretation of the underlying physiological signals (Drolet et al. 2008; Hilker et al. 2008; Middleton et al. 2009, 2016; Hilker et al. 2011).

Due to the complexity of canopy structure, some important leaf traits (e.g., nitrogen content) may not always be directly detectable at stand scales (Knyazikhin et al. 2013). However, because foliar nitrogen levels indirectly influence canopy structure, nitrogen levels can often be inferred, even when not directly measured, with remote sensing (Ollinger et al. 2008; Ollinger 2011; Townsend et al. 2013). These examples of leaf traits correlating with higher level traits demonstrate that a proper understanding of the particular context can facilitate the assessment of plant function from remote sensing, even when the underlying leaf traits are not directly detectable at larger scales. Consequently, even at larger scales sampled by aircraft and satellite, the concept of leaf traits can have utility, and can often be expressed in suites of characteristics that collectively define "plant strategies" (Grime 2006) or "optical types" (Ustin and Gamon 2010), both variations on the plant functional type concept. Vegetation functional types are commonly used in many global models of ecosystem function and Earth system science as a way to classify complex vegetation biophysical properties into a few simplified "types," facilitating model simulations (Bonan et al. 2002, 2003; Pavlick et al. 2013; van Bodegom et al. 2014). The concept of vegetation *optical types*, sometimes called *spectral types* or *spectral species* (Feret and Asner 2014), represents an attempt to define functionally significant optical properties (or spectral patterns) related to plant traits. In this way, defining vegetation functional types in terms of optical types (spectral types) can simplify studies of large-scale vegetation processes.

Advances in spectroscopy and statistical techniques have led to reliable methods to assess leaf traits, sometimes rivalling traditional metrics involving structural or wet chemical measurements. Traits can be derived from specific spectral regions using vegetation indices (Table 1; Fig. 2) (e.g. Malenovský et al. 2013). Alternatively, traits can be retrieved from optical measurements using statistical approaches such as partial least squares regression (PLSR, Roelofsen et al. 2014; Serbin et al. 2014). However, these methods have not yet revealed universal relationships. Part of the reason lies in the evolutionary convergence of plant traits; many plant species have evolved similar solutions to the same environmental challenges, and it is often the subtle variation in these features over time or across environmental gradients that can be most informative. Most published studies linking optical properties and plant traits are limited to a single point in time, generally near the center of the growing season (Homolová et al. 2013). Thus, they fail to capture the full variation in conditions or plant traits expressed in the life of an individual organism, canopy, stand, or ecosystem. Not surprisingly, results from one season do not always apply well to datasets collected in another season (Chavana-Bryant et al. 2017). Until we obtain extensive, and uniform, time series of optical data, the full evaluation of plant traits through optical properties will remain a work in progress. Fully understanding the links between spectral space and trait space represents an ongoing challenge, in part due to the large data volume, involving many traits and spectral features along with other independent variables (e.g., time, space, and observation geometry). While progress is being made on the definition and application of optical types (Gamon et al. 1997; Ustin and Gamon 2010; Feret and Asner 2014), we currently lack a comprehensive theory of optical types, or a full understanding

of how they relate to plant traits. Opportunities lie in the full exploration of the effects of temporal and spatial scales, a topic more fully explored below (see Sect. 7).

Plant traits can also be related to spectra through forward physical modeling (Schneider et al. 2014) and inversion of leaf or coupled leaf-canopy radiative transfer models at the leaf level (e.g., PROSPECT, Jacquemoud and Baret 1990; Malenovský et al. 2006), or the canopy level using one-dimensional models (e.g., SAIL, Verhoef 1984; or SCOPE, van der Tol et al. 2009) or three-dimensional models (e.g., DART, Gastellu-Etchegorry et al. 2017). For more detailed discussion of such models, see Verrelst et al. (2019) and Malenovský et al. (2019) (both in this volume).

4 Proximal Spectrometry

Many of the current advances in spectral reflectance for vegetation function are derived from proximal spectrometers. These include handheld portable spectrometers and ground-based imaging spectrometers (Pinto et al. 2016, 2017), as well as instruments mounted on towers (Hilker et al. 2011), mobile platforms (Gamon et al. 2006; Sims et al. 2006), and unmanned aircraft vehicles (UAVs, also known as drones; Burkart et al. 2014; Lucieer et al. 2014; Malenovský et al. 2017). Many of these studies have been coordinated with flux tower observations, facilitating calibrations with independent data and cross-site comparisons (see reviews by Gamon et al. 2010; Balzarolo et al. 2011; Gamon 2015).

A key advantage of proximal sampling has been its ability to provide rich time series of data, which have been difficult to obtain using airborne or satellite platforms. These instruments sample at scales that can be readily related to leaf traits and where process measurements (e.g., carbon or water vapor fluxes, changing pigment content, or dynamic chlorophyll fluorescence) can be independently validated using experimental approaches and coupled measurements at similar scales. They are also particularly well suited to exploring the functional regulatory, ontogenetic and physiological mechanisms that underlie changes in optical properties at larger scales. Hence, proximal instruments provide useful experimental tools to explore new ways to sample vegetation function and to validate optical measurements at larger scales. A disadvantage is their restricted spatial coverage, limited distribution across biomes and vegetation types, and lack of standardization in sensors and protocols, making it difficult to draw general conclusions from individual field studies (Gamon et al. 2010; Gamon 2015). The large number of these studies, combined with improved informatics and statistical or other modeling tools for upscaling, promise to advance our understanding of vegetation function, particularly when combined with aircraft or satellite observations. Proximal sensing can also lead to innovation in sensor technologies and applications that can inform the design and interpretation of future airborne or spaceborne sensors.

5 Airborne Remote Sensing

Increasingly, airborne imaging spectrometers are being applied to assess vegetation traits and functional processes. These instruments typically collect measurements in either the "full-range" VSWIR (visible-short-wave infrared) wavelengths or in the more limited VNIR (visible-near-infrared) range. Full-range sensors offer a wider range of options for detecting plant traits, but are more expensive, heavier, and more difficult to maintain and operate. VNIR

| Journal : **SmallCondensed 10712** | Article No : **9511** | Pages : **25** | MS Code : **GEOP-D-18-00002** | Dispatch : **11-2-2019** |

Surveys in Geophysics

240 sensors, while more limited in spectral coverage, are much lighter and less expensive, provid-
241 ing an easier entry point into the world of airborne imaging spectrometry. Depending upon
242 their intended purpose, these instruments range in spectral resolution from 10 nm for typical
243 reflectance applications to ≤ 0.3 nm in the case of airborne spectrometers intended for detec-
244 tion of solar-induced fluorescence (SIF, Rascher et al. 2015; Schaepman et al. 2015; Wieneke
245 et al. 2016). Pixel sizes (IFOV) can approximate to 1 m^2, a scale fine enough to resolve indi-
246 vidual plant canopies in the case of large trees. This combination of fine spatial and spectral
247 resolution is particularly useful for evaluating spatial patterns in plant traits (Asner and Martin
248 2016).

249 From the perspective of vegetation dynamics, a primary limitation of airborne platforms
250 has been the difficulty and expense of obtaining regular observations to yield sufficiently large
251 and frequent time series of vegetation function. Typical airborne datasets contain single over-
252 passes, or at best a handful of measurements over a short time span (e.g., several within-day,
253 or "diurnal" acquisitions), which are obtained a few times in a single growing season. Such
254 limited temporal frequency restricts the power for assessing functional processes occurring
255 at different time scales. On the other hand, even single aircraft overpasses can provide useful
256 assessments of spatial patterns in functional traits (Homolová et al. 2014; Asner and Martin
257 2016) illustrating the benefits of inferring function from trait-based approaches.

258 Airborne field campaigns with various generations of the Airborne Visible/InfraRed imag-
259 ing Spectrometer (AVIRIS) sensor, such as the AVIRIS Classic and the AVIRIS-NG, have
260 provided good examples of the power of imaging spectrometry to detect vegetation function.
261 Many of these campaigns have assessed plant function through photosynthesis, water status
262 (Fuentes et al. 2006; Serbin et al. 2015; Somers et al. 2015; Asner et al. 2016a), or nutrient sta-
263 tus (Asner and Vitousek 2005). The HyPlant airborne sensor (Rascher et al. 2015), developed
264 in preparation for the forthcoming FLEX satellite mission (Kraft et al. 2013; Drusch et al.
265 2017), with an expected launch in late 2022, provides very high spectral resolution radiance or
266 reflectance suitable to detect chlorophyll fluorescence and foliar pigment content, both power-
267 ful indicators of photosynthetic activity (Rossini et al. 2015; Simmer et al. 2015; Wieneke
268 et al. 2016; Middleton et al. 2017). The Airborne Prism Experiment (APEX), serving as an
269 airborne precursor for a space-based imaging spectrometer mission, demonstrates simultane-
270 ous high-resolution spectroscopic retrievals for the atmosphere, the non-vegetated surface, and
271 chlorophyll fluorescence (Schaepman et al. 2015). Numerous airborne campaigns focusing on
272 plant traits have provided promising tests of trait-based approaches to assess vegetation func-
273 tion (Asner et al. 2016b; Schneider et al. 2017). Despite limited revisit time, airborne spec-
274 trometry remains a powerful tool for demonstrating the ability of full-spectral information to
275 improve our understanding of vegetation function. Emerging monitoring networks, such as the
276 NEON program (funded by the US National Science Foundation), are beginning to provide
277 airborne imaging spectrometry capability along with proximal spectral measurements across a
278 network of sites in the continental US, offering new opportunities for the systematic explora-
279 tion of vegetation function across scales for representative ecosystems (Kampe et al. 2010).

6 Satellite Remote Sensing

6.1 Brief History of Optical Satellites for Vegetation Monitoring

282 Historically, spatially and temporally extensive series of spectral imagery from space use-
283 ful for assessing vegetation function have been limited to a few of the over 1000 global

284 orbiting satellites. Most of these have had limited spectral coverage, constraining their util-
285 ity for vegetation functional studies. Many of the multi-spectral orbiting sensors have been
286 radiometers with a small number (e.g., 2–8) of relatively wide (e.g., $\geq$ 20–30 nm) spectral
287 bands related to a handful of biophysical traits, some related to green vegetation struc-
288 ture (e.g., LAI and fPAR, Table 1). Long-term repetitive observations have been obtained
289 by the USGS Landsat Thematic Mapper/Enhanced Thematic Mapper (TM/ETM) series,
290 and the NOAA Advanced Very High Resolution Radiometer (AVHRR) series. Despite the
291 fact that the NOAA missions, built primarily for weather observations, were not designed
292 or optimized for vegetation monitoring, they fortuitously have provided important insights
293 into vegetation function over large regions. The discovery that a combination of red and
294 near-infrared wavelengths used together could track seasonality of green vegetation bio-
295 mass and leaf area index (Rouse et al. 1974; Tucker 1979), has been applied to the interpre-
296 tation of AVHRR imagery at continental and global scales, providing a revolutionary view
297 of vegetation functional dynamics at continental scales (Tucker et al. 1985), and allowing
298 globally consistent vegetation classifications incorporating seasonal dynamics (DeFries
299 and Townshend 1994).

300 The MODIS (Moderate Resolution Imaging Spectroradiometer) carried on the Terra
301 (launched in 1999) and Aqua (launched in 2002) satellites have emerged as important sen-
302 sors for global biospheric monitoring. At its conception in the 1990s, the MODIS data sys-
303 tem EOSDIS (the Earth Observing System Data and Information System) was the "largest
304 and most complex data system every constructed" (Marshall 1993). Key to MODIS's suc-
305 cess has been the availability of standardized data products, enabling the establishment of
306 a critical terrestrial database spanning many years that has led to scientific advancements
307 in many earth science disciplines. The operational collection and processing of 36 spectral
308 bands across the full shortwave and infrared regions from the Terra and Aqua MODIS have
309 yielded invaluable time series of atmospheric, marine, and terrestrial products. These 36
310 bands include 20 reflective shortwave and 16 emitted infrared bands. Seven of the reflective
311 bands are used for terrestrial and atmospheric monitoring land discrimination, covering the
312 VSWIR spectral regions, with varying bandwidths (20–50 nm, Fig. 3). Some of these are
313 used to provide a few key land products, including LAI and FPAR that are widely used
314 in studies of vegetation dynamics (Table 1). Additionally, nine narrower (10 nm) "ocean
315 color" bands in the visible spectrum (blue bands, Fig. 3) are also part of the MODIS suite
316 at coarser spatial scales (~ 1 km for nadir views). These ocean bands were not originally
317 intended for vegetation applications, and in earlier MODIS Collections (1–5), they were
318 processed separately from land bands. Consequently, until recently, researchers using the
319 "ocean" bands for terrestrial vegetation studies have had to conduct their own processing
320 and atmospheric corrections, a situation rectified with Collection 6.

321 Global vegetation products developed from MODIS, including the NDVI, the Enhanced
322 Vegetation Index (EVI; Huete et al. 2002) and related products such as leaf area index
323 (LAI) and the fraction of absorbed photosynthetically active radiation (fPAR, or fAPAR;
324 Myneni et al. 2002), are used to derive gross and net primary production (GPP and NPP)
325 (Table 1). These spectrally based products have been used extensively for assessing
326 regional and global vegetation functional dynamics, including photosynthetic activity and
327 stress or disturbance responses. A key example is the MODIS MOD17 NPP product, based
328 on the light-use efficiency (LUE) model, which provides the first consistent, multi-year
329 depictions of global terrestrial NPP (Running et al. 2004), describing both seasonal phe-
330 nology and interannual variation in vegetation photosynthetic activity at continental scales,
331 allowing attribution of NPP anomalies to the El Niño–Southern Oscillation (ENSO),
332 drought and other climate factors (Zhao and Running 2010).
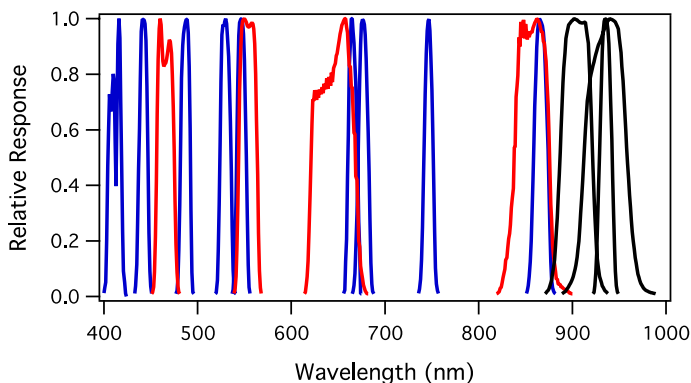
Fig. 3 Normalized spectral response functions of the MODIS sensors showing ocean bands (blue), land bands (red), and atmospheric bands (black)

333   New MODIS products for vegetation function continue to emerge. Although MODIS
334 ocean bands were not originally intended for vegetation, the recent MAIAC reprocessing
335 (Lyapustin et al. 2011a, b), as part of MODIS Collection 6, now provides surface reflec-
336 tance products from both land and ocean bands over terrestrial regions from each MODIS
337 sensor at daily time steps at the equator and multiple times a day in high latitudes due
338 to orbital overlap near the poles. Several studies have demonstrated that combining land
339 and ocean bands over terrestrial regions offers improved assessments of plant traits linked
340 to photosynthetic activity (Rahman et al. 2004; Drolet et al. 2008; Garbulsky et al. 2008;
341 Goerner et al. 2009; Gamon et al. 2016; Middleton et al. 2016). While this new band com-
342 bination still lacks the spectral detail needed to assess many specific plant traits, it con-
343 tains sufficient information to detect relative chlorophyll and carotenoid pigment levels,
344 important indicators of plant stress and photosynthetic activity. This new information on
345 plant pigment ratios improves our assessment of photosynthetic phenology, particularly for
346 evergreen vegetation, which has been difficult to assess using greenness indices like NDVI
347 (Gamon et al. 2016). Similarly, a new MODIS product, fAPARchl (the fAPAR fraction
348 attributable to chlorophyll only), has been developed (Zhang et al. 2009, 2013, 2016) and
349 has been proposed as a standard product. These findings are consistent with a history of
350 studies showing that retrievals of plant pigments from remote sensing provide useful infor-
351 mation about vegetation photosynthesis, productivity, stress, and overall health (Gitelson
352 et al. 2005; Ustin et al. 2009). In global, cross-biome comparisons, NIRv, a new combina-
353 tion of red and NIR band reflectance from MODIS, yields improved GPP estimates relative
354 to the NDVI (Badgley et al. 2017). These newly emerging indices are a testament to the
355 value of consistent satellite time series and a persistent, accessible data system for advanc-
356 ing our understanding of vegetation function.
357   Since the historical satellite records contain imagery collected with only a few wide
358 spectral bands, they cannot distinguish many important vegetation functional traits and
359 processes detectable only with narrow-band (≤ 10 nm) spectral features. Furthermore,
360 many of the satellite products are temporally aggregated; largely to address problems with
361 varying cloud cover and sensor view angles, past MODIS EVI and NDVI products have
362 been primarily available as composite values at 16-day (and recently at 8-day) time steps,
363 which limits their ability to detect temporal dynamics, particularly during periods of rapid
364 change (e.g., spring green-up or unexpected disturbance events) (Gamon et al. 2013).

365 Newer MODIS collections (e.g., Collection 6) offer daily time series of MODIS reflectance
366 products, enabling a finer look at vegetation dynamics that offers to better resolve these
367 events. Another limitation of the historical satellite time series has been the requirement
368 to integrate other data (e.g., meteorological data) collected from different instruments on
369 different temporal and spatial scales to facilitate quantitative interpretation of the spectral
370 information (Running et al. 2004; Heinsch et al. 2006). Consequently, while current multi-
371 band satellite products reveal broad patterns of a few key emergent properties of terrestrial
372 ecosystems and biomes at the regional to global scales, they are not able to resolve detailed
373 processes at the scale of individual land management units, or at specific experimental sites
374 within observational networks (e.g., the flux tower network). Consequently, many underly-
375 ing *mechanisms* remain partly obscured, leaving gaps in our understanding of vegetation
376 function.

377 Despite their limitations, these global satellite products have demonstrated the power
378 of consistent global surface reflectance products for assessment of terrestrial photosyn-
379 thetic dynamics. While many underlying mechanisms remain hidden due to their coarse
380 sampling scales, the consistent time series over many decades has provided an invaluable
381 perspective on vegetation change and essential vegetation fields for global Earth system
382 models (Garonna et al. 2016). These models include Dynamic Global Vegetation Models
383 (DGVMs, e.g., Bonan et al. 2003; Pavlick et al. 2013; van Bodegom et al. 2014), soil–veg-
384 etation–atmosphere-transfer (SVAT) models depicting surface–atmosphere interactions
385 (Arora 2002), nested physiological-climate models (Sellers et al. 1996a, b), and global
386 models of net primary production (NPP, Running et al. 2004). This power to reveal vegeta-
387 tion function is continually being expanded with new reanalyses, and by adding additional
388 satellite data.

389 Since 2015, a follow-on satellite to continue the MODIS record is the Joint Polar Satel-
390 lite System, with a Visible Infrared Imaging Radiometer Suite (VIIRS). Unfortunately, this
391 satellite has fewer bands than MODIS, limiting its utility for vegetation functional assess-
392 ment. Today, the Copernicus Sentinel program of the European Space Agency (ESA) for
393 the European Commission (EC) is setting new standards for operational multi-spectral
394 Earth Observation with Sentinel-2 and Sentinel-3 (Aschbacher and Milagro-Pérez 2012;
395 Malenovský et al. 2012). The two synchronously flying satellites Sentinel-2A and Senti-
396 nel-2B provide 12 optical bands with a spatial resolution of 10–30 meters and a global
397 revisiting time of less than 5 days (Drusch et al. 2012). Besides these operational flagships
398 of ESA, the recently launched (August 2017) VENµS mini-satellite (Israel Space Agency
399 and CNES, France) offers 12 spectral bands (16–40 nm wide) and a unique orbit revisit
400 scheme.

6.2 Hyperspectral Satellites

402 In recent years, several satellite missions demonstrating the capability of imaging spec-
403 trometers, also known as hyperspectral scanners, have been placed in orbit. These mis-
404 sions have provided limited geographical coverage, with imagery collected on user request,
405 and include the NASA EO-1/Hyperion and the ESA CHRIS Proba. The Hyperion sen-
406 sor provided limited image data collection at 30-m spatial resolution upon user request
407 over a 17-year lifespan (2000–2017). All of these datasets are now freely available through
408 the USGS archive. Recent analyses from the Hyperion collection demonstrate the power
409 of imaging spectrometry for evaluating spatial patterns of net ecosystem CO_2 exchange
410 (Campbell et al. 2013) and also vegetation functional types based on spectral patterns

(Somers and Asner 2012; Huemmrich et al. 2013). The Compact High Resolution Imaging Spectrometer (CHRIS) sensor has a multi-angular viewing capability (2 forward, a nadir and 2 backward viewing angles) for a better understanding of the bidirectional reflectance distribution function (BRDF) of terrestrial surfaces. It collects up to 150 channels (spectral range of 400–1050 nm) with a ground sampling resolution of 17 or 34 m over preselected sites on demand since 2001. A VIS-NIR spectrometer, the Hyperspectral Imager for the Coastal Ocean (HICO), was flown (2009–2014) on the International Space Station (ISS), and its utility for ecosystem function was demonstrated by Huemmrich et al. (2017).

The hyperspectral or spectroscopic observations acquired from space thus far have provided a strong foundation for the further development of satellite imaging spectrometers with global coverage. Hyperspectral missions of note include the Medium Resolution Imaging Spectrometer (MERIS), which had 15 programmable bands (FWHM ~ 2.5–30 nm) and flew from 2002 to 2012, and the CHRIS-Proba which has 200 narrow bands that can be combined into wider (e.g., 18) bands at varying spatial coverage ≤ 30 m. The two European Sentinel-3 satellites continue the mission concept of MERIS with an increasing number of optical bands (21 vs. 15 bands) and an improved optical performance (Donlon et al. 2012). The DLR Earth Sensing Imaging Spectrometer (DESIS; Eckardt et al. 2015) sponsored by the German Space Agency, was deployed on the International Space Station in June 2018. Additional proposed spaceborne imaging spectrometers promise to further expand our understanding of vegetation function using detectors with much higher spectral, spatial and temporal resolution. Presently, there are several new missions in various stages of planning or deployment. The space agencies of Italy and Israel are preparing the PRISMA mission (Amato et al. 2013) for launch in 2018–2019. The EnMAP mission (Germany) (Guanter et al. 2015a) and NASA's HyspIRI (Hyperspectral Infrared Imager) mission, (Lee et al. 2015), recently evolved into the Surface Biology and Geology (SBG) mission, will follow in the next few years. These emerging satellite instruments offer much richer spectral information than the history of multi-band Earth observation satellites mentioned above, and promise to expand the opportunities for assessing specific plant functional traits and dynamics.

6.3 Solar-Induced Fluorescence (SIF)

Recent examples of fortuitous applications of satellite data to assess vegetation function have arisen from several very high spectral resolution but coarse spatial resolution global satellite sensors designed for atmospheric gas sampling, including the Greenhouse gases Observing SATellite (GOSAT), the Global Ozone Monitoring Experiment-2 (GOME-2), and NASA's Orbiting Carbon Observatory (OCO-2). These instruments have extremely high spectral resolution (< 0.5 nm) with the capability of resolving solar Fraunhofer lines and atmospheric (telluric) absorption features that enable detection and quantification of a tiny solar-induced chlorophyll fluorescence (SIF) signal emitted from vegetation. This SIF signal increases with the amount of radiation absorbed by chlorophyll (APAR), and decreases with the amount of absorbed radiation that is dissipated as heat within leaves under stress (Porcar-Castell et al. 2014), providing a direct link to photosynthetic activity (gross primary productivity). These "ultra-spectral" sensors used for SIF detection offer new possibilities for global assessment of terrestrial photosynthesis or gross primary production (GPP), albeit at very coarse temporal and spatial scales (Frankenberg et al. 2011; Joiner et al. 2011; Guanter et al. 2012). A primary drawback of these global satellites has been that retrieval of the weak fluorescence signals requires averaging over large time steps

457 and regions of the planet, obscuring fine-scale dynamics needed to explain underlying
458 mechanism. This limitation is spurring development of new sensors and applications of
459 spectrometry and fluorometry from airborne (Rascher et al. 2015; Schaepman et al. 2015)
460 and proximal platforms (Burkart et al. 2014, 2015; Wyber et al. 2017). These ongoing
461 advances combining airborne and proximal remote sensing offer to further clarify the func-
462 tional links between passive fluorescence (SIF) and seasonally dynamic pigments levels
463 (Gamon et al. 2016; Springer et al. 2017). Our growing understanding of photosynthetic
464 dynamics will be further improved with the enhanced capabilities of the newly launched
465 TROPOMI sensor (Guanter et al. 2015b), and the planned European Space Agency's
466 FLEX (Fluoresence Explorer) satellite mission, designed specifically to directly address
467 pigments and SIF simultaneously at global scales (Kraft et al. 2013; Drusch et al. 2017).

7 Current Challenges and Opportunities

469 A primary challenge in the remote sensing of vegetation function lies in extracting reliable,
470 quantitative metrics of functional properties and processes that can be universally applied.
471 Part of this challenge derives from the fact that remote sensing methods typically oper-
472 ate at spatial and temporal scales different from the functional processes or traits of inter-
473 est (Fig. 1). Remarkably, despite this scale mismatch, plant traits and processes can often
474 still be detected, even if the underlying mechanisms of signal transmission and detection
475 remain partly unclear (Townsend et al. 2013; Schweiger et al. 2017). Developing a better
476 understanding of the reasons for this convergence across scales, and understanding why it
477 succeeds in some cases and fails in other cases, remain fundamental tasks. Potential solu-
478 tions can be found in applying the full range of instrumentation from proximal sensors to
479 global satellites to address scaling methods. Additional solutions lie in integrating physical,
480 biological, and statistical approaches, and further exploring the concept of "optical types,"
481 representations of plant traits through patterns in spectral reflectance (Ustin and Gamon
482 2010), also called "spectral types" or "spectral species" (Feret and Asner 2014). Due to the
483 multiple dimensions and high volume of data involved, greater attention to informatics will
484 be needed. These challenges and opportunities are discussed in more detail below.

7.1 Integrating Trait-Based and Process-Based Approaches

486 The divergent methods to assess vegetation function based on static traits versus dynamic
487 processes often seem to be distinct conceptual and practical approaches. However, these
488 perspectives can be combined for greater insight, and a current opportunity lies in integrat-
489 ing trait- and process-based approaches. Traits, while sometimes applied categorically, can
490 be depicted along a continuum (Wright et al. 2004). This continuum also has a time dimen-
491 sion (Chavana-Bryant et al. 2017). Capturing the full temporal dynamics of plant traits,
492 while rarely attempted, can provide better insights into vegetation processes. The lack of
493 consistent time series of optical properties, except for some proximal ground- or tower-
494 based datasets, limits our current understanding of plant function using remote sensing.
495 The advent of global imaging spectrometers with regular repeat cycles will greatly expand
496 our understanding of vegetation processes at multiple scales, particularly when combined
497 with proximal and airborne spectrometers. Similarly, spectral patterns can reveal informa-
498 tion on both states and processes, allowing community properties like spectral diversity
499 to be related to ecosystem processes like productivity (Wang et al. 2016a, b). In this way,

500 integrating traits and processes can help quantify functional diversity (Schneider et al.
501 2017, Schweiger et al. 2017, 2018) and inform our understanding of ecosystem services
502 (Braun et al. 2017).

7.2 Bridging Spatial and Temporal Scales

504 To what extent leaf traits can be detected at canopy or larger landscape scales observed by
505 global spaceborne missions remains an open question, with good evidence both for and
506 against upscaling of functional traits. The current literature on this topic is not entirely
507 clear, with some authors questioning the detectability of certain leaf traits using optical
508 remote sensing (Knyazikhin et al. 2013) and others noting that they could be detected under
509 the right conditions (Townsend et al. 2013). Not all optical traits scale equally; multiple
510 light scattering and absorption of plant canopies can confound some features, but accentu-
511 ate other features allowing some leaf traits but not others to be easily detectable at canopy
512 and stand scales. A number of studies report detection of plant functional traits with air-
513 borne imaging spectrometry (Asner et al. 2016a, b; Schneider et al. 2017), but the question
514 remains: What exactly is detected as we move to progressively larger scales? A more com-
515 plete answer to this question requires a clear methodology with well-defined hypotheses
516 and conceptual frameworks, as well as physical models simulating imaging spectroscopy
517 signals.

518 Scaling limitations are being transcended with new computational methods and sam-
519 pling approaches. Since remote sensing technology (including observational instruments,
520 computational power, and physical and statistical models) is rapidly changing, the topic of
521 how to assess function across scales needs to be periodically revisited and updated. New
522 statistical methods, including advanced machine learning approaches, are emerging that
523 are greatly facilitating data analysis across scales (Verrelst et al. 2016). Improved compre-
524 hensive mathematical approaches to scaling (e.g., physically based radiative transfer mod-
525 els) are also relevant, as described in Verrelst et al. (2019) and Malenovský el al. (2019)
526 (this issue).

527 While these models capture static vegetation biophysical and structural properties well,
528 most do not adequately describe transient dynamics in plant functional properties medi-
529 ated by physiological processes, such as chloroplast movement, leaf movement or rapid
530 biochemical and changes associated with light regulation. Although some models are capa-
531 ble of resolving complex photon–vegetation interactions in three-dimensional (3D) space
532 (Gastellu-Etchegorry et al. 2017), they cannot provide the same flexibility and realism that
533 can be obtained from dynamic empirical measurements. Development of new hybrid mod-
534 els is a move in the right direction, where radiative transfer with simulations of dynamic
535 energy budgets at the canopy/landscape scale is combined with photosynthetic biochemical
536 models describing functional leaf optical properties tied to physiological regulation at the
537 leaf scale (e.g., SCOPE, Timmermans et al. 2013). This direction should be considered in
538 models accounting for 3D spatial heterogeneity, which can help us to better understand the
539 impact that less dynamic structural features have on the ability to detect rapidly changing
540 biochemical physiological processes. The development of GUI-driven models, such as the
541 Automated Radiative Transfer Models Operator (ARTMO, http://ipl.uv.es/artmo/) offer-
542 ing wider accessibility in a user-friendly format, represents a recent advance that offers to
543 facilitate the application of models to questions of vegetation function. In all cases, outputs

544 of model simulations need to be tested against empirical measurements for a wide range of
545 vegetation types to help clarify underlying mechanisms.

546   Clearly, the topic of scaling functional traits needs further study. Because spectra are
547 temporally dynamic, often displaying considerable redundancy (leading to collinear
548 responses), and because plants exhibit functional convergence (Ollinger 2011), it is easy
549 to get the right answer for the wrong reason (or vice versa), i.e., because of non-causal
550 relationships. Without attention to scale, traditional mapping approaches, while they may
551 imply functional differences, may not be sufficient to fully detect functional processes, in
552 part due to complexities of spatial scale, but also due to the temporal dynamics of plant
553 traits (Chavana-Bryant et al. 2017). Unless temporal dynamics are fully considered, there
554 will remain some question as to the accuracy of plant functional characterization.

555 ### 7.3 Conceptual Advances in Integrating Physical and Biological Approaches

556 An understanding of the scaling questions would benefit from an integration of ecological
557 theory with physical principles of radiative transfer (Kattenborn et al. 2017), but this has
558 yet to be fully accomplished. While a complete radiative transfer modeling capability will
559 have to consider complex physical and physiological processes (e.g., turbulent air trans-
560 fer and the rapid physiological responses to dynamic light regimes), it can also be better
561 guided by ecological theory that can help explain how canopies, stands, and landscapes are
562 constructed from underlying rules guiding plant evolution and adaptation.

563   Ecological theory states that form follows function. This principle, which has some-
564 times been labeled "functional convergence" (Field 1991; Ollinger 2011), allows us to
565 detect functional patterns and differences with imaging spectrometry. An elaboration of
566 this concept states that plant biochemistry and structure have evolved to meet the func-
567 tional goal of efficient resource capture and organism protection (among other goals), and
568 that detectable differences in these traits with remote sensing reflect different adaptations
569 or evolutionary responses, or "strategies" (Grime 2006). Fundamentally, this is an eco-
570 nomic argument, stating that plants tend to follow economic rules when displaying func-
571 tional properties (Bloom et al. 1985). The scaling of plant traits can be guided by principles
572 of functional convergence, which can involve coordination of plant traits that simplify the
573 challenge of addressing plant function from remote sensing. Different functional solutions
574 can be addressed by a clearer definition of optical types representing optically detectable
575 suites of functionally important plant traits. A better integration of theory with models and
576 empirical measurements will be needed to accomplish these goals.

577 ### 7.4 Informatics Needs for Databases, Archives, Tools, and Protocols

578 Spectral assessment of vegetation function presents new challenges for informatics in the
579 collection, storage, processing, and archiving of increasingly large data volumes. This
580 challenge exists both for the trait-based approach, where large numbers of plant traits are
581 being assessed with reflectance spectra, and for the process-based approaches, where the
582 additional demands of time-series analyses arise. Currently, unlike the development of
583 databases and related tools that are broadly used by the molecular, genetics, and bioin-
584 formatics communities, there is currently no single, widely accepted set of versatile, but
585 standardized data tools for the remote sensing community, greatly hampering advances in
586 this area. While rudimentary online spectral libraries for vegetation are available, most of
587 these cannot easily accommodate large volumes of spectral time series or image data. Most

588 existing spectral libraries focus on a few static *types* (the archetypal mean). However, for
589 functional analysis, we are often more interested in the *variation* over time and space (vari-
590 ance), which is not easily accommodated in current databases. While image databases exist
591 for most satellite sensors, there is no similar community database or archival solution for
592 the variety of current and emerging airborne or field imaging spectrometers, hampering
593 our sharing and understanding of imaging spectroscopy for addressing plant function in
594 a broader context. Both basic research and emerging applications, including phenotyping
595 and precision farming, would greatly benefit from effective data management and process-
596 ing solutions, which remain sparse to date. Examples include the SPECCHIO database
597 (Hueni et al. 2009, 2011). The terrestrial remote sensing community could learn from other
598 disciplines (e.g., astrophysics), where effective community solutions for handling and shar-
599 ing large spectral datasets have been developed (Munari et al. 2005; Rayner et al. 2009).

8 Societal Benefits and Global Challenges

601 Further development of remote sensing tools for vegetation functional assessment would
602 provide multiple benefits, both to basic science and to society. Vegetation plays a key role
603 in many global Earth system processes, ranging from biogeochemical cycles to the sur-
604 face–atmosphere transport of mass and energy that regulates our atmosphere and climate.
605 Vegetation also supports diverse biological communities and provides many essential eco-
606 system goods and services. Until we can reliably monitor vegetation function at all scales,
607 we cannot fully understand these processes and contributions or how they are changing.
608 For example, longstanding questions about the role of the terrestrial biosphere as a carbon
609 sink, and whether we should expect that sink to start relaxing, thereby accelerating climate
610 change (Schimel 2007) could be better answered with improved remote sensing tools for
611 addressing vegetation function. Similarly, remote sensing offers promising new and inte-
612 grative ways of assessing biodiversity (Cavender-Bares et al. 2017), species composition
613 (Asner and Vitousek 2005), and emerging diseases (Calderón et al. 2013; Zarco-Tejada
614 et al. 2018) in a changing world. Many promising applications and management practices,
615 including phenotyping, precision agriculture, and early stress and disease detection, could
616 be better addressed with well-designed optical remote sensing methods geared toward
617 accurate, precise, and timely vegetation monitoring and related analytics tools. Develop-
618 ment of novel imaging spectroscopy-based remote sensing methods for vegetation function
619 will be essential for monitoring and maintaining healthy and resilient ecosystems in chang-
620 ing world, providing concurrent social and economic benefits.

References

Amato U, Antoniadis A, Carfora MF, Colandrea P, Cuomo V, Franzese M, Pignatti S, Serio C (2013) Statistical classification for assessing PRISMA hyperspectral potential for agricultural land use. IEEE J Sel Top Appl Earth Observ Remote Sens 6:615–625

Arora V (2002) Modeling vegetation as a dynamic component in soil–vegetation–atmosphere transfer schemes and hydrological models. Rev Geophys. https://doi.org/10.1029/2001rg000103

Aschbacher J, Milagro-Pérez MP (2012) The European Earth monitoring (GMES) programme: status and perspectives. Remote Sens Environ 120:3–8

Asner GP, Martin RE (2016) Spectranomics: emerging science and conservation opportunities at the interface of biodiversity and remote sensing. Glob Ecol Conserv 8:212–219. https://doi.org/10.1016/j.gecco.2016.09.010

Asner GP, Vitousek PM (2005) Remote analysis of biological invasion and biogeochemical change. Proc Natl Acad Sci USA 102:4383–4386. https://doi.org/10.1073/pnas.0500823102

Asner GP, Brodrick PG, Anderson CB, Vaughn N, Knapp DE, Martin RE (2016a) Progressive forest canopy water loss during the 2012–2015 California drought. Proc Natl Acad Sci USA 113:E249–E255. https://doi.org/10.1073/pnas.1523397113

Asner GP, Knapp DE, Anderson CB, Martin RE, Vaughn N (2016b) Large-scale climatic and geophysical controls on the leaf economics spectrum. Proc Natl Acad Sci USA 113:E4043–E4051. https://doi.org/10.1073/pnas.1604863113

Badgley G, Field CB, Berry JA (2017) Canopy near-infrared reflectance and terrestrial photosynthesis. Sci Adv 3:5. https://doi.org/10.1126/sciadv.1602244

Balzarolo M et al (2011) Ground-based optical measurements at European flux sites: a review of methods, instruments and current controversies. Sensors 11:7954–7981. https://doi.org/10.3390/s110807954

Barton CVM, North PRJ (2001) Remote sensing of canopy light use efficiency using the photochemical reflectance index—model and sensitivity analysis. Remote Sens Environ 78:264–273. https://doi.org/10.1016/s0034-4257(01)00224-3

Battaglia M, Cherry ML, Beadle CL, Sands PJ, Hingston A (1998) Prediction of leaf area index in eucalypt plantations: effects of water stress and temperature. Tree Physiol 18:521–528

Bloom AJ, Chapin FS, Mooney HA (1985) Resource limitation in plants—an economic analogy. Annu Rev Ecol Syst 16:363–392. https://doi.org/10.1146/annurev.es.16.110185.002051

Bonan GB, Levis S, Kergoat L, Oleson KW (2002) Landscapes as patches of plant functional types: an integrating concept for climate and ecosystem models. Glob Biogeochem Cycles. https://doi.org/10.1029/2000gb001360

Bonan GB, Levis S, Sitch S, Vertenstein M, Oleson KW (2003) A dynamic global vegetation model for use with climate models: concepts and description of simulated vegetation dynamics. Glob Change Biol 9:1543–1566. https://doi.org/10.1046/j.1365-2486.2003.00681.x

Braun D et al (2017) From instantaneous to continuous: using imaging spectroscopy and in situ data to map two productivity-related ecosystem services. Ecol Indic 82:409–419. https://doi.org/10.1016/j.ecolind.2017.06.045

Burkart A, Cogliati S, Schickling A, Rascher U (2014) A novel UAV-based ultra-light weight spectrometer for field spectroscopy. IEEE Sens J 14:62–67. https://doi.org/10.1109/jsen.2013.2279720

Burkart A et al (2015) A method for uncertainty assessment of passive sun-induced chlorophyll fluorescence retrieval using an infrared reference light. IEEE Sens J 15:4603–4611. https://doi.org/10.1109/jsen.2015.2422894

Calderón R, Navas-Cortés JA, Lucena C, Zarco-Tejada PJ (2013) High-resolution airborne hyperspectral and thermal imagery for early detection of Verticillium wilt of olive using fluorescence, temperature and narrow-band spectral indices. Remote Sens Environ 139:231–245. https://doi.org/10.1016/j.rse.2013.07.031

Campbell PKE et al (2013) EO-1 hyperion reflectance time series at calibration and validation sites: stability and sensitivity to seasonal dynamics. IEEE J Sel Top Appl Earth Obs Remote Sens 6:276–290. https://doi.org/10.1109/jstars.2013.2246139

Cavender-Bares J, Gamon JA, Hobbie SE, Madritch MD, Meireles JE, Schweiger AK, Townsend PA (2017) Harnessing plant spectra to integrate the biodiversity sciences across biological and spatial scales. Am J Bot 104:966–969. https://doi.org/10.3732/ajb.1700061

Chavana-Bryant C et al (2017) Leaf aging of Amazonian canopy trees as revealed by spectral and physiochemical measurements. New Phytol 214:1049–1063. https://doi.org/10.1111/nph.13853

Cornelissen JHC et al (2003) A handbook of protocols for standardised and easy measurement of plant functional traits worldwide. Aust J Bot 51:335–380. https://doi.org/10.1071/bt02124

de Wit CT (1970) Dynamic concepts in biology. In: Setlik I (ed) Prediction and measurement of photosynthetic productivity. Centre for Agricultural Publishing and Documentation, Wageningen, pp 17–23

DeFries RS, Townshend JRG (1994) NDVI-derived land cover classifications at a global scale. Int J Remote Sens 15:3567–3586

Donlon C et al (2012) The global monitoring for environment and security (GMES) Sentinel-3 mission. Remote Sens Environ 120:37–57. https://doi.org/10.1016/j.rse.2011.07.024

Drolet GG et al (2008) Regional mapping of gross light-use efficiency using MODIS spectral indices. Remote Sens Environ 112:3064–3078. https://doi.org/10.1016/j.rse.2008.03.002

Drusch M et al (2012) Sentinel-2: ESA's optical high-resolution mission for GMES operational services. Remote Sens Environ 120:25–36. https://doi.org/10.1016/j.rse.2011.11.026

Drusch M et al (2017) The FLuorescence EXplorer Mission Concept-ESA's Earth Explorer 8. IEEE Trans Geosci Remote Sens 55:1273–1284. https://doi.org/10.1109/tgrs.2016.2621820

Eckardt A et al (2015) DESIS (DLR Earth Sensing Imaging Spectrometer for the ISS-MUSES platform). In: 2015 IEEE international geoscience and remote sensing symposium (IGARSS), pp 1457–1459

Ehleringer JR, Comstock J (1987) Leaf absorptance and leaf angle: mechanisms for stress avoidance. In: Tenhunen JD, Catarino FM, Lange OL, Oechel WC (eds) Plant response to stress: functional analysis in Mediterranean ecosystems. Springer, Berlin, pp 55–76

Ehleringer JR, Field CB (1993) Scaling physiological processes: leaf to globe, 1st edn. Academic Press, New York

Enquist BJ et al (2015) Scaling from traits to ecosystems: developing a general trait driver theory via integrating trait-based and metabolic scaling theories. In: Pawar S, Woodward G, Dell AI (eds) Advances in ecological research, vol 52. Academic Press, New York, pp 249–318. https://doi.org/10.1016/bs.aecr.2015.02.001

Feilhauer H, Somers B, van der Linden S (2017) Optical trait indicators for remote sensing of plant species composition: predictive power and seasonal variability. Ecol Indic 73:825–833. https://doi.org/10.1016/j.ecolind.2016.11.003

Feret JB, Asner GP (2014) Mapping tropical forest canopy diversity using high-fidelity imaging spectroscopy. Ecol Appl 24:1289–1296

Field CB (1991) Ecological scaling of carbon gain to stress and resource availability. In: Mooney HA, Winner WE, Pell EJ (eds) Response of plants to multiple stresses. Physiological ecology. Academic Press, New York, pp 35–65

Frankenberg C et al (2011) New global observations of the terrestrial carbon cycle from GOSAT: patterns of plant fluorescence with gross primary productivity. Geophys Res Lett 38:6. https://doi.org/10.1029/2011gl048738

Fuentes DA et al (2006) Mapping carbon and water vapor fluxes in a chaparral ecosystem using vegetation indices derived from AVIRIS. Remote Sens Environ 103:312–323. https://doi.org/10.1016/j.rse.2005.10.028

Gamon JA (2015) Reviews and syntheses: optical sampling of the flux tower footprint. Biogeosciences 12:4509–4523. https://doi.org/10.5194/bg-12-4509-2015

Gamon JA, Surfus JS (1999) Assessing leaf pigment content and activity with a reflectometer. New Phytol 143:105–117. https://doi.org/10.1046/j.1469-8137.1999.00424.x

Gamon JA, Qiu HL (1999) Ecological applications of remote sensing at multiple scales. In: Pugnaire F, Valladares F (eds) Handbook of functional plant ecology. Marcel Dekker Inc., New York, pp 805–846

Gamon JA, Serrano L, Surfus JS (1997) The photochemical reflectance index: an optical indicator of photosynthetic radiation use efficiency across species, functional types, and nutrient levels. Oecologia 112:492–501. https://doi.org/10.1007/s004420050337

Gamon JA, Field CB, Fredeen AL, Thayer S (2001) Assessing photosynthetic downregulation in sunflower stands with an optically-based model. Photosynth Res 67:113–125. https://doi.org/10.1023/a:1010677605091

Gamon JA, Cheng YF, Claudio H, MacKinney L, Sims DA (2006) A mobile tram system for systematic sampling of ecosystem optical properties. Remote Sens Environ 103:246–254. https://doi.org/10.1016/j.rse.2006.04.006

Gamon JA et al (2010) SpecNet revisited: bridging flux and remote sensing communities. Can J Remote Sens 36:S376–S390

Gamon JA, Huemmrich KF, Stone RS, Tweedie CE (2013) Spatial and temporal variation in primary productivity (NDVI) of coastal Alaskan tundra: decreased vegetation growth following earlier snowmelt. Remote Sens Environ 129:144–153. https://doi.org/10.1016/j.rse.2012.10.030

Gamon JA et al (2016) A remotely sensed pigment index reveals photosynthetic phenology in evergreen conifers. Proc Natl Acad Sci USA 113:13087–13092. https://doi.org/10.1073/pnas.1606162113

Garbulsky MF, Peñuelas J, Papale D, Filella I (2008) Remote estimation of carbon dioxide uptake by a Mediterranean forest. Glob Change Biol 14:2860–2867. https://doi.org/10.1111/j.1365-2486.2008.01684.x

Garonna I, de Jong R, Schaepman ME (2016) Variability and evolution of global land surface phenology over the past three decades (1982–2012). Glob Change Biol 22:1456–1468. https://doi.org/10.1111/gcb.13168

Gastellu-Etchegorry JP et al (2017) DART: recent advances in remote sensing data modeling with atmosphere, polarization, and chlorophyll fluorescence. IEEE J Sel Top Appl Earth Obs Remote Sens 10:2640–2649. https://doi.org/10.1109/jstars.2017.2685528

Gitelson AA, Vina A, Ciganda V, Rundquist DC, Arkebauer TJ (2005) Remote estimation of canopy chlorophyll content in crops. Geophys Res Lett 32:L08403. https://doi.org/10.1029/2005gl022688

Gitelson AA, Gamon JA, Solovchenko A (2017) Multiple drivers of seasonal change in PRI: Implications for photosynthesis 2. Stand level. Remote Sens Environ 190:198–206. https://doi.org/10.1016/j.rse.2016.12.015

Goerner A, Reichstein M, Rambal S (2009) Tracking seasonal drought effects on ecosystem light use efficiency with satellite-based PRI in a Mediterranean forest. Remote Sens Environ 113:1101–1111. https://doi.org/10.1016/j.rse.2009.02.001

Goetz SJ, Bunn AG, Fiske GJ, Houghton RA (2005) Satellite-observed photosynthetic trends across boreal North America associated with climate and fire disturbance. Proc Natl Acad Sci USA 102:13521–13525. https://doi.org/10.1073/pnas.0506179102

Grime JP (2006) Plant strategies, vegetation processes, and ecosystem properties. Wiley, New York

Guanter L et al (2012) Retrieval and global assessment of terrestrial chlorophyll fluorescence from GOSAT space measurements. Remote Sens Environ 121:236–251. https://doi.org/10.1016/j.rse.2012.02.006

Guanter L et al (2015a) The EnMAP spaceborne imaging spectroscopy mission for earth observation. Remote Sens 7:8830–8857. https://doi.org/10.3390/rs70708830

Guanter L et al (2015b) Potential of the TROPOspheric Monitoring Instrument (TROPOMI) onboard the Sentinel-5 Precursor for the monitoring of terrestrial chlorophyll fluorescence. Atmos Meas Tech 8:1337–1352. https://doi.org/10.5194/amt-8-1337-2015

Heinsch FA et al (2006) Evaluation of remote sensing based terrestrial productivity from MODIS using regional tower eddy flux network observations. IEEE Trans Geosci Remote Sens 44:1908–1925. https://doi.org/10.1109/tgrs.2005.853936

Hilker T, Coops NC, Hall FG, Black TA, Wulder MA, Nesic Z, Krishnan P (2008) Separating physiologically and directionally induced changes in PRI using BRDF models. Remote Sens Environ 112:2777–2788. https://doi.org/10.1016/j.rse.2008.01.011

Hilker T, Gitelson A, Coops NC, Hall FG, Black TA (2011) Tracking plant physiological properties from multi-angular tower-based remote sensing. Oecologia 165:865–876. https://doi.org/10.1007/s00442-010-1901-0

Homolová L, Malenovský Z, Clevers J, Garcia-Santos G, Schaepman ME (2013) Review of optical-based remote sensing for plant trait mapping. Ecol Complex 15:1–16. https://doi.org/10.1016/j.ecocom.2013.06.003

Homolová L, Schaepman ME, Lamarque P, Clevers J, de Bello F, Thuiller W, Lavorel S (2014) Comparison of remote sensing and plant trait-based modelling to predict ecosystem services in subalpine grasslands. Ecosphere. https://doi.org/10.1890/es13-00393.1

Huemmrich KF, Gamon JA, Tweedie CE, Campbell PKE, Landis DR, Middleton EM (2013) Arctic tundra vegetation functional types based on photosynthetic physiology and optical properties. IEEE J Sel Top Appl Earth Obs Remote Sens 6:265–275. https://doi.org/10.1109/jstars.2013.2253446

Huemmrich KF, Campbell PKE, Gao BC, Flanagan LB, Goulden M (2017) ISS as a platform for optical remote sensing of ecosystem carbon fluxes: a case study using HICO. IEEE J Sel Top Appl Earth Obs Remote Sens 10:4360–4375. https://doi.org/10.1109/jstars.2017.2725825

Hueni A, Nieke J, Schopfer J, Kneubuehler M, Itten K (2009) The spectral database SPECCHIO for improved long term usability and data sharing. Comput Geosci 35(3):557–565. https://doi.org/10.1016/j.cageo.2008.03.015

Hueni A, Malthus T, Kneubuehler M, Schaepman M (2011) Data exchange between distributed spectral databases. Comput Geosci 37:861–873. https://doi.org/10.1016/j.cageo.2010.12.009

Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG (2002) Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ 83:195–213. https://doi.org/10.1016/s0034-4257(02)00096-2

Jacquemoud S, Baret F (1990) PROSPECT: a model of leaf optical properties spectra. Remote Sens Environ 34:75–91. https://doi.org/10.1016/0034-4257(90)90100-z

Jacquemoud S et al (2009) PROSPECT plus SAIL models: a review of use for vegetation characterization. Remote Sens Environ 113:S56–S66. https://doi.org/10.1016/j.rse.2008.01.026

Jarvis P (1993) Prospects for bottom up models. In: Ehleringer JR, Field CB (eds) Scaling physiological processes: leaf to globe, 1st edn. Academic Press, New York, pp 115–126

Joiner J, Yoshida Y, Vasilkov AP, Yoshida Y, Corp LA, Middleton EM (2011) First observations of global and seasonal terrestrial chlorophyll fluorescence from space. Biogeosciences 8:637–651. https://doi.org/10.5194/bg-8-637-2011

Jung M et al (2011) Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations. J Geophys Res Biogeosci. https://doi.org/10.1029/2010jg001566

Kampe TU, Johnson BR, Kuester M, Keller M (2010) NEON: the first continental-scale ecological observatory with airborne remote sensing of vegetation canopy biochemistry and structure. J Appl Remote Sens. https://doi.org/10.1117/1.3361375

Kattenborn T, Fassnacht FE, Pierce S, Lopatin J, Grime JP, Schmidtlein S (2017) Linking plant strategies and plant traits derived by radiative transfer modelling. J Veg Sci 28:717–727. https://doi.org/10.1111/jvs.12525

Kattge J et al (2011) TRY—a global database of plant traits. Glob Change Biol 17:2905–2935. https://doi.org/10.1111/j.1365-2486.2011.02451.x

Knyazikhin Y et al (2013) Hyperspectral remote sensing of foliar nitrogen content. Proc Natl Acad Sci USA 110:E185–E192. https://doi.org/10.1073/pnas.1210196109

Kraft S et al (2013) FLORIS: phase A status of the fluorescence imaging spectrometer of the Earth Explorer mission candidate FLEX. In: Conference on sensors, systems, and next-generation satellites XVII, Dresden, Germany, 23–26 Sept 2013. Proceedings of SPIE. https://doi.org/10.1117/12.2032060

Lee CM, Cable ML, Hook SJ, Green RO, Ustin SL, Mandl DJ, Middleton EM (2015) An introduction to the NASA Hyperspectral InfraRed Imager (HyspIRI) mission and preparatory activities. Remote Sens Environ 167:6–19. https://doi.org/10.1016/j.rse.2015.06.012

Levin SA (1992) The problem of pattern and scale in ecology. Ecology 73:1943–1967. https://doi.org/10.2307/1941447

Lucieer A, Malenovsky Z, Veness T, Wallace L (2014) HyperUAS-Imaging spectroscopy from a multirotor unmanned aircraft system. J Field Robot 31:571–590. https://doi.org/10.1002/rob.21508

Lyapustin A, Martonchik J, Wang Y, Laszlo I, Korkin S (2011a) Multiangle implementation of atmospheric correction (MAIAC): 1. Radiative transfer basis and look-up tables. J Geophys Res Atmos. https://doi.org/10.1029/2010jd014985

Lyapustin A et al (2011b) Multiangle implementation of atmospheric correction (MAIAC): 2. Aerosol algorithm. J Geophys Res Atmos. https://doi.org/10.1029/2010jd014986

Malenovský Z, Albrechtova J, Lhotakova Z, Zurita-Milla R, Clevers J, Schaepman ME, Cudlin P (2006) Applicability of the PROSPECT model for Norway spruce needles. Int J Remote Sens 27:5315–5340. https://doi.org/10.1080/01431160600762990

Malenovský Z, Rott H, Cihlar J, Schaepman ME, Garcia-Santos G, Fernandes R, Berger M (2012) Sentinels for science: potential of Sentinel-1, -2, and -3 missions for scientific observations of ocean, cryosphere, and land. Remote Sens Environ 120:91–101. https://doi.org/10.1016/j.rse.2011.09.026

Malenovský Z et al (2013) Retrieval of spruce leaf chlorophyll content from airborne image data using continuum removal and radiative transfer. Remote Sens Environ 131:85–102. https://doi.org/10.1016/j.rse.2012.12.015

Malenovský Z, Lucieer A, King DH, Turnbull JD, Robinson SA (2017) Unmanned aircraft system advances health mapping of fragile polar vegetation. Methods Ecol Evol 8:1842–1857. https://doi.org/10.1111/2041-210x.12833

Malenovský Z, Homolová L, Lukeš P, Buddenbaum H, Verrelst J, Alonso L, Schaepman ME, Lauret N, Gastellu-Etchegorry JP (2019) Variability and uncertainty challenges in upscaling imaging spectroscopy observations from leaves to vegetation canopies. Surv Geophys (in review; this issue)

Marshall E (1993) Global change—fitting planet earth into a user-friendly database. Science 261:846. https://doi.org/10.1126/science.261.5123.846

Middleton EM, Cheng Y-B, Hilker T, Black TA, Krishnan P, Coops NC, Huemmrich KF (2009) Linking foliage spectral responses to canopy-level ecosystem photosynthetic light-use efficiency at a Douglas-fir forest in Canada. Can J Remote Sens 35:166–188

Middleton EM, Huemmrich KF, Landis DR, Black TA, Barr AG, McCaughey JH (2016) Photosynthetic efficiency of northern forest ecosystems using a MODIS-derived Photochemical Reflectance Index (PRI). Remote Sens Environ 187:345–366. https://doi.org/10.1016/j.rse.2016.10.021

Middleton EM et al (2017) The 2013 FLEX-US airborne campaign at the Parker Tract loblolly pine plantation in North Carolina, USA. Remote Sens. https://doi.org/10.3390/rs9060612

Munari U, Sordo R, Castelli F, Zwitter T (2005) An extensive library of 2500–10500 Å synthetic spectra. Astron Astrophys 442:1127–1134. https://doi.org/10.1051/0004-6361:20042490

Myneni RB et al (2002) Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. Remote Sens Environ 83:214–231. https://doi.org/10.1016/s0034-4257(02)00074-3

Ollinger SV (2011) Sources of variability in canopy reflectance and the convergent properties of plants. New Phytol 189:375–394. https://doi.org/10.1111/j.1469-8137.2010.03536.x

Ollinger SV (2008) Canopy nitrogen, carbon assimilation, and albedo in temperate and boreal forests: functional relations and potential climate feedbacks. Proc Natl Acad Sci USA 105:19336–19341. https://doi.org/10.1073/pnas.0810021105

Pavlick R, Drewry DT, Bohn K, Reu B, Kleidon A (2013) The Jena Diversity-Dynamic Global Vegetation Model (JeDi-DGVM): a diverse approach to representing terrestrial biogeography and biogeochemistry based on plant functional trade-offs. Biogeosciences 10:4137–4177. https://doi.org/10.5194/bg-10-4137-2013

Pinto F et al (2016) Sun-induced chlorophyll fluorescence from high-resolution imaging spectroscopy data to quantify spatio-temporal patterns of photosynthetic function in crop canopies. Plant, Cell Environ 39:1500–1512. https://doi.org/10.1111/pce.12710

Pinto F, Müller-Linow M, Schickling A, Cendrero-Mateo MP, Ballvora A, Rascher U (2017) Multiangular observation of canopy sun-induced chlorophyll fluorescence combining imaging spectroscopy and stereoscopy. Remote Sens 9, article no. 415. https://doi.org/10.3390/rs9050415

Porcar-Castell A et al (2014) Linking chlorophyll a fluorescence to photosynthesis for remote sensing applications: mechanisms and challenges. J Exp Bot 65:4065–4095. https://doi.org/10.1093/jxb/eru191

Quattrochi DA, Goodchild MF (1997) Scale in remote sensing and GIS. CRC Press, Boca Raton

Rahman AF, Cordova VD, Gamon JA, Schmid HP, Sims DA (2004) Potential of MODIS ocean bands for estimating CO_2 flux from terrestrial vegetation: a novel approach. Geophys Res Lett. https://doi.org/10.1029/2004gl019778

Rascher U et al (2015) Sun-induced fluorescence—a new probe of photosynthesis: first maps from the imaging spectrometer. HyPlant Glob Change Biol 21:4673–4684. https://doi.org/10.1111/gcb.13017

Rayner JT, Cushing MC, Vacca WD (2009) The infrared telescope facility (IRTF) spectral library: cool stars. Astrophys J Suppl 185:289–432. https://doi.org/10.1088/0067-0049/185/2/289

Reich PB, Ellsworth DS, Walters MB (1998) Leaf structure (specific leaf area) modulates photosynthesis-nitrogen relations: evidence from within and across species and functional groups. Funct Ecol 12:948–958. https://doi.org/10.1046/j.1365-2435.1998.00274.x

Roelofsen HD, van Bodegom PM, Kooistra L, Witte JPM (2014) Predicting leaf traits of herbaceous species from their spectral characteristics. Ecol Evol 4:706–719. https://doi.org/10.1002/ece3.932

Rossini M et al (2015) Red and far red Sun-induced chlorophyll fluorescence as a measure of plant photosynthesis. Geophys Res Lett 42:1632–1639. https://doi.org/10.1002/2014gl062943

Rouse JW, Haas RH, Schell JA, Deering DW (1974) Monitoring vegetation systems in the Great Plains with ERTS. Remote Sensing Center, Texas A&M University, College Station

Running SW, Nemani RR, Heinsch FA, Zhao MS, Reeves M, Hashimoto H (2004) A continuous satellite-derived measure of global terrestrial primary production. Bioscience 54:547–560. https://doi.org/10.1641/0006-3568(2004)054%5b0547:acsmog%5d2.0.co;2

Schaepman ME et al (2015) Advanced radiometry measurements and earth science applications with the Airborne Prism Experiment (APEX). Remote Sens Environ 158:207–219. https://doi.org/10.1016/j.rse.2014.11.014

Schimel D (2007) Carbon cycle conundrums. Proc Natl Acad Sci USA 104:18353–18354. https://doi.org/10.1073/pnas.0709331104

Schneider FD, Letterer R, Morsdorf F, Gastellu-Etchegorry JP, Lauret N, Pfeifer N, Schaepman ME (2014) Simulating imaging spectrometer data: 3D forest modeling based on LiDAR and in situ data. Remote Sens Environ 152:235–250. https://doi.org/10.1016/j.rse.2014.06.015

Schneider FD, Morsdorf F, Schmid B, Petchey OL, Hueni A, Schimel DS, Schaepman ME (2017) Mapping functional diversity from remotely sensed morphological and physiological forest traits. Nat Commun. https://doi.org/10.1038/s41467-017-01530-3

Schull MA, Anderson MC, Houborg R, Gitelson A, Kustas WP (2015) Thermal-based modeling of coupled carbon, water, and energy fluxes using nominal light use efficiencies constrained by leaf chlorophyll observations. Biogeosciences 12:1511–1523. https://doi.org/10.5194/bg-12-1511-2015

Schweiger AK, Schutz M, Risch AC, Kneubuhler M, Haller R, Schaepman ME (2017) How to predict plant functional types using imaging spectroscopy: linking vegetation community traits, plant functional types and spectral response. Methods Ecol Evol 8:86–95. https://doi.org/10.1111/2041-210x.12642

Schweiger AK et al (2018) Plant spectral diversity integrates functional and phylogenetic components of biodiversity and predicts ecosystem function. Nat Ecol Evol 2:976. https://doi.org/10.1038/s41559-018-0551-1

Sellers PJ et al (1996a) Comparison of radiative and physiological effects of doubled atmospheric CO_2 on climate. Science 271:1402–1406. https://doi.org/10.1126/science.271.5254.1402

Sellers PJ, Los SO, Tucker CJ, Justice CO, Dazlich DA, Collatz GJ, Randall DA (1996b) A revised land surface parameterization (SiB2) for atmospheric GCMs. Part II: the generation of global fields of terrestrial biophysical parameters from satellite data. J Clim 9:706–737. https://doi.org/10.1175/1520-0442(1996)009%3c0706:arlspf%3e

Sellers PJ et al (1997) BOREAS in 1997: experiment overview, scientific results, and future directions. J Geophys Res Atmos 102:28731–28769. https://doi.org/10.1029/97jd03300

Serbin SP, Dillaway DN, Kruger EL, Townsend PA (2012) Leaf optical properties reflect variation in photosynthetic metabolism and its sensitivity to temperature. J Exp Bot 63:489–502. https://doi.org/10.1093/jxb/err294

Serbin SP, Singh A, McNeil BE, Kingdon CC, Townsend PA (2014) Spectroscopic determination of leaf morphological and biochemical traits for northern temperate and boreal tree species. Ecol Appl 24:1651–1669

Serbin SP et al (2015) Remotely estimating photosynthetic capacity, and its response to temperature, in vegetation canopies using imaging spectroscopy. Remote Sens Environ 167:78–87. https://doi.org/10.1016/j.rse.2015.05.024

Serrano L, Ustin SL, Roberts DA, Gamon JA, Peñuelas J (2000) Deriving water content of chaparral vegetation from AVIRIS data. Remote Sens Environ 74:570–581. https://doi.org/10.1016/s0034-4257(00)00147-4

Simmer C et al (2015) Monitoring and modeling the terrestrial system from pores to catchments: the transregional collaborative research center on patterns in the soil–vegetation–atmosphere system. Bull Am Meteorol 96:1765–1787. https://doi.org/10.1175/bams-d-13-00134.1

Sims DA, Gamon JA (2003) Estimation of vegetation water content and photosynthetic tissue area from spectral reflectance: a comparison of indices based on liquid water and chlorophyll absorption features. Remote Sens Environ 84:526–537. https://doi.org/10.1016/s0034-4257(02)00151-7

Sims DA, Luo HY, Hastings S, Oechel WC, Rahman AF, Gamon JA (2006) Parallel adjustments in vegetation greenness and ecosystem CO_2 exchange in response to drought in a Southern California chaparral ecosystem. Remote Sens Environ 103:289–303. https://doi.org/10.1016/j.rse.2005.01.020

Singh A, Serbin SP, McNeil BE, Kingdon CC, Townsend PA (2015) Imaging spectroscopy algorithms for mapping canopy foliar chemical and morphological traits and their uncertainties. Ecol Appl 25:2180–2197. https://doi.org/10.1890/14-2098.1.sm

Somers B, Asner GP (2012) Hyperspectral time series analysis of native and invasive species in Hawaiian rainforests. Remote Sens 4:2510–2529. https://doi.org/10.3390/rs4092510

Somers B, Asner GP, Martin RE, Anderson CB, Knapp DE, Wright SJ, Van De Kerchove R (2015) Mesoscale assessment of changes in tropical tree species richness across a bioclimatic gradient in Panama using airborne imaging spectroscopy. Remote Sens Environ 167:111–120. https://doi.org/10.1016/j.rse.2015.04.016

Springer KR, Wang R, Gamon JA (2017) Parallel seasonal patterns of photosynthesis, fluorescence, and reflectance indices in boreal trees. Remote Sens. https://doi.org/10.3390/rs9070691

Street LE, Shaver GR, Williams M, Van Wijk MT (2007) What is the relationship between changes in canopy leaf area and changes in photosynthetic CO_2 flux in arctic ecosystems? J Ecol 95:139–150. https://doi.org/10.1111/j.1365-2745.2006.01187.x

Stylinski CD, Gamon JA, Oechel WC (2002) Seasonal patterns of reflectance indices, carotenoid pigments and photosynthesis of evergreen chaparral species. Oecologia 131:366–374. https://doi.org/10.1007/s00442-002-0905-9

Teuling AJ, Seneviratne SI (2008) Contrasting spectral changes limit albedo impact on land-atmosphere coupling during the 2003 European heat wave. Geophys Res Lett. https://doi.org/10.1029/2007gl032778

| Journal : **SmallCondensed 10712** | Article No : **9511** | Pages : **25** | MS Code : **GEOP-D-18-00002** | Dispatch : **11-2-2019** |

Surveys in Geophysics

Timmermans J, Su Z, van der Tol C, Verhoef A, Verhoef W (2013) Quantifying the uncertainty in estimates of surface-atmosphere fluxes through joint evaluation of the SEBS and SCOPE models. Hydrol Earth Syst Sci 17:1561–1573. https://doi.org/10.5194/hess-17-1561-2013

Townsend PA, Serbin SP, Kruger EL, Gamon JA (2013) Disentangling the contribution of biological and physical properties of leaves and canopies in imaging spectroscopy data. Proc Natl Acad Sci USA 110:E1074–E1074. https://doi.org/10.1073/pnas.1300952110

Tucker CJ (1979) Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens Environ 8:127–150. https://doi.org/10.1016/0034-4257(79)90013-0

Tucker CJ, Townshend JRG, Goff TE (1985) African land-cover classification using satellite data. Science 227:369–375. https://doi.org/10.1126/science.227.4685.369

Ustin SL, Gamon JA (2010) Remote sensing of plant functional types. New Phytol 186:795–816. https://doi.org/10.1111/j.1469-8137.2010.03284.x

Ustin SL, Gitelson AA, Jacquemoud S, Schaepman M, Asner GP, Gamon JA, Zarco-Tejada P (2009) Retrieval of foliar information about plant pigment systems from high resolution spectroscopy. Remote Sens Environ 113:S67–S77. https://doi.org/10.1016/j.rse.2008.10.019

van Bodegom PM, Douma JC, Verheijen LM (2014) A fully traits-based approach to modeling global vegetation distribution. Proc Natl Acad Sci USA 111:13733–13738. https://doi.org/10.1073/pnas.1304551110

van der Tol C, Verhoef W, Timmermans J, Verhoef A, Su Z (2009) An integrated model of soil-canopy spectral radiances, photosynthesis, fluorescence, temperature and energy balance. Biogeosciences 6:3109–3129. https://doi.org/10.5194/bg-6-3109-2009

Verhoef W (1984) Light scattering by leaf layers with application to canopy reflectance modeling: the SAIL model. Remote Sens Environ 16:125–141. https://doi.org/10.1016/0034-4257(84)90057-9

Verrelst J et al (2019) Quantifying vegetation biophysical variables from imaging spectroscopy data: a review on retrieval methods. Surv Geophys 1–41. https://doi.org/10.1007/s10712-018-9478-y (this issue)

Verrelst J, Dethier S, Rivera JP, Munoz-Mari J, Camps-Valls G, Moreno J (2016) Active learning methods for efficient hybrid biophysical variable retrieval. IEEE Geosci Remote Sens Lett 13:1012–1016. https://doi.org/10.1109/lgrs.2016.2560799

Wang WM, Li ZL, Su HB (2007) Comparison of leaf angle distribution functions: effects on extinction coefficient and fraction of sunlit foliage. Agric For Meteorol 143:106–122. https://doi.org/10.1016/j.agrformet.2006.12.003

Wang R, Gamon JA, Emmerton CA, Li HT, Nestola E, Pastorello GZ, Menzer O (2016a) Integrated analysis of productivity and biodiversity in a southern Alberta prairie. Remote Sens. https://doi.org/10.3390/rs8030214

Wang R et al (2016b) Seasonal variation in the NDVI-species richness relationship in a prairie grassland experiment (Cedar Creek). Remote Sens 8:1. https://doi.org/10.3390/rs8020128

Wieneke S, Ahrends H, Damm A, Pinto F, Stadler A, Rossini M, Rascher U (2016) Airborne based spectroscopy of red and far-red sun-induced chlorophyll fluorescence: implications for improved estimates of gross primary productivity. Remote Sens Environ 184:654–667. https://doi.org/10.1016/j.rse.2016.07.025

Williamson SN, Barrio IC, Hik DS, Gamon JA (2016) Phenology and species determine growing-season albedo increase at the altitudinal limit of shrub growth in the sub-Arctic. Glob Change Biol 22:3621–3631. https://doi.org/10.1111/gcb.13297

Wright IJ et al (2004) The worldwide leaf economics spectrum. Nature 428:821–827. https://doi.org/10.1038/nature02403

Wyber R, Malenovský Z, Ashcroft MB, Osmond B, Robinson SA (2017) Do daily and seasonal trends in leaf solar induced fluorescence reflect changes in photosynthesis, growth or light exposure? Remote Sens. https://doi.org/10.3390/rs9060604

Zarco-Tejada PJ et al (2018) Previsual symptoms of *Xylella fastidiosa* infection revealed in spectral plant-trait alterations. Nat Plants 4:432–439. https://doi.org/10.1038/s41477-018-0189-7

Zhang QY, Middleton EM, Margolis HA, Drolet GG, Barr AA, Black TA (2009) Can a satellite-derived estimate of the fraction of PAR absorbed by chlorophyll (FAPAR(chl)) improve predictions of light-use efficiency and ecosystem photosynthesis for a boreal aspen forest? Remote Sens Environ 113:880–888. https://doi.org/10.1016/j.rse.2009.01.002

Zhang QY, Middleton EM, Cheng YB, Landis DR (2013) Variations of foliage chlorophyll fAPAR and foliage non-chlorophyll fAPAR (fAPARchl, fAPARnon-chl) at the Harvard Forest. IEEE J Sel Top Appl Earth Obs Remote Sens 6:2254–2264. https://doi.org/10.1109/jstars.2013.2275176

Zhang Q et al (2016) Integrating chlorophyll fAPAR and nadir photochemical reflectance index from EO-1/Hyperion to predict cornfield daily gross primary production. Remote Sens Environ 186:311–321. https://doi.org/10.1016/j.rse.2016.08.026

Zhao M, Running SW (2010) Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. Science 329:940–943. https://doi.org/10.1126/science.1192666

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

REVISED PROOF

 Springer